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Making Noisy Data Sing

A Micro Approach to Measuring Industrial Efficiency

James R. Tybout

An approach to measuring industrial plant efficiency that recognizes and deals with data imperfections — including measurement errors, missing observations, and selectivity bias.

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Technical, scale, and allocative inefficiency are widely believed to plague the industrial sectors of developing countries. Tybout presents a way to measure this inefficiency with imperfect data.

There is great interest in documenting the patterns and magnitudes of inefficiency, so that appropriate corrective policies can be designed. But most relevant empirical work has been done at the sectoral level. So making accurate measurements and distinguishing between different dimensions of performance is difficult.

Recently micro survey data have become available, so plant-level studies that more directly measure the dimensions of efficiency have begun to emerge. But these studies are often flawed because survey data from developing countries are often rife with measurement error, missing observations, and selectivity bias.

Tybout presents a new approach to analyzing plant efficiency that recognizes and deals with such data imperfections. It should interest students of productivity and technological efficiency in both developing and developed countries.

Tybout has developed full-information maximum-likelihood (FIML) estimators of production technologies that deal with missing data and measurement errors, making alternative assumptions about the missing data patterns and the timing of employment and decisions.

These estimators yield indices of the returns to scale, mean square deviation from the efficient frontier, and — when labor is treated as endogenous — mean square deviation from efficient factor mixes.

To gauge the performance of the alternative estimators, Tybout applies them to census data on Chilean industry, and compares the results with "naive" estimators that do not recognize data imperfections.

This paper, a product of the Trade Policy Division, Country Economics Department, is part of a larger effort in PPR to quantify linkages between trade liberalization and changes in industrial sector performance. It was prepared for the research project "Industrial Competition, Productive Efficiency, and their Relation to Trade Regimes" (RPO 674-46). Copies are available free from the World Bank, 1818 H Street NW, Washington DC 20433. Please contact Maria Ameal, room N10-035, extension 61465 (31 pages with tables).

Making Noisy Data Sing:
Estimating Production Technologies in Developing Countries

by
James R. Tybout*

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This paper was prepared for the World Bank research project "Industrial Competition, Productive Efficiency, and Their Relation to Trade Regimes," (RPO 674-46).

A. OVERVIEW

It is widely held that technical inefficiency, scale inefficiency, and allocative inefficiency plague the industrial sectors of less developed countries (LDCs). Accordingly, there is considerable interest in documenting the patterns and magnitudes of these problems, so that appropriate corrective policies can be designed. However, most of the relevant empirical work has been done at the sectoral level, resulting in serious aggregation problems, and an inability to distinguish between the different dimensions of performance.[1]

Recently, as micro survey data have become available, plant level studies that measure the dimensions of efficiency more directly have begun to emerge (e.g., Pitt and Lee (1981), Corbo and de Melo (1985), and Chen and Tang (1987)).[2] But because survey data from LDCs are often rife with measurement error, missing observations, and selectivity bias, these studies have suffered from their own serious shortcomings. This paper develops a new approach to plant-level analysis of efficiency that recognizes and deals with such data imperfections. It should be of interest not only to students of productivity in LDCs, but also to those who study technology and

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1/ Attempts to measure productive efficiency with sectoral and macro data from LDCs are reviewed in Page and Nishimizu (1987), Pack (1988) and Chenery et al (1986).

2/ Techniques for measuring technical and allocative efficiency with micro data are reviewed by Forsund, Lovell and Schmidt (1980) and Schmidt (1985).

efficiency in the industrialized countries using less-than-perfect data.[3]

The focus of the analysis is on two basic problems with plant-level data. First, inflation distortions and bookkeeping conventions create significant discrepancies between observed and actual values of capital stocks. This not only makes standard production parameter estimators inconsistent, it distorts the residual term of the production function, upon which technical efficiency analysis is largely based.[4] Second, many plants simply do not report their capital stock figures, or fail to report rented components like land and buildings. These "holes" in the data reduce the power of standard estimators, and unless explicitly dealt with, can also introduce selectivity bias.

This study proposes full-information maximum-likelihood (FIML) estimators of production technologies that correct for both of these basic data problems, making alternative assumptions regarding the endogeneity of labor and missing data patterns. The estimators yield indices of the returns to scale, mean square deviation from the

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3/ For example, Griliches and Mairesse (1988) are unable to identify stable production technologies with industrial census data from the United States, France, and Japan. They conclude (inter alia) "we need to figure out ways of allowing for the discrepancy between recorded inputs and actually used levels . . . "

4/ Curiously, the technical efficiency literature has recognised measurement error in output (e.g., Schmidt, 1985, on "stochastic frontier" models), but has generally ignored measurement error in capital, which is likely to be much larger.

efficient frontier, and (when labor is treated as endogenous) mean square deviation from efficient factor mixes. To gauge the performance of the alternative estimators, they are applied to Chilean industrial census data, and compared with "naive" estimators that do not recognize data imperfections.

The paper is organized into 5 remaining sections and an appendix. Section B lays out assumptions about technology and producer behavior. Section C deals with corrections for measurement error, and section D generalizes the approach to deal with missing data. Section E further generalizes by treating employment as endogenous, and finally, section F reports applications of the various estimtors to Chilean census data. Appendices provide covariance matrices and other details.

B. TECHNOLOGY AND PRODUCER BEHAVIOR

We begin with a simple representation of technology. For the i^{th} enterprise, let Q_i denote the logarithm of value added, K^*_i denote the logarithm of "true" capital stock, E_i be the logarithm of employment (measured in "efficiency units", e.g., Griliches and Ringstad, 1971), and D_i be a vector of dummies that control for things like plant ownership and regional location. Within a given industry, assume these variables are related to one another by the following Cobb-Douglas production function:[5]

5/ The Cobb-Douglas technology is chosen because census data are unlikely to support more elaborate functional forms (Griliches and Ringstad, 1971), and it affords maximimum flexibility in dealing with data imperfections. The analysis in this paper could be carried through equally well for a short-run Cobb-Douglas cost function, in which variable cost is expressed as a function of output and capital.

$$(1) \qquad Q_i = K_i^* \alpha + \begin{bmatrix} 1 \\ D_i \\ E_i \end{bmatrix}' \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix} + u_{1i}, \quad \text{or more compactly,}$$

$$Q_i = K_i^* \alpha + L_i' \beta + u_{1i}$$

Here α and β are a scalar and a conformable column vector, respectively, $L_i = [1, D_i, E_i]'$, and u_1 is a random disturbance reflecting some combination of technical efficiency, measurement error in Q, and peculiarities of the enterprise's production process.

Some serially correlated aspects of plant productivity (like machine age) may be observable to managers but not to econometricians. Hence it is instructive to decompose the disturbance u_1 into a component that managers are able to observe prior to the production period ($\bar{u}_{1i}$), and a component that reflects everything else:

$$u_{1i} = \bar{u}_{1i} + \epsilon_{1i}$$

Assume that both components are normal, and $\text{cov}(\bar{u}_{1i}, \epsilon_{1i}) = E(\bar{u}_{1i}) = E(\epsilon_{1i}) = 0$ for all i.

It remains to characterize producer behavior, and to thereby develop interpretations for the disturbances in estimated equations. Suppose employment (E) is variable in the short run, and at the beginning of each production period, managers hire the amount of labor that maximizes median profits. Also, let the expected real wage (in logarithms) be related to its actual <u>ex post</u> value at the i^{th} plant by:

$$W_i^e = W_i + \epsilon_{2i}$$

Then the observed employment level at the i^{th} plant is:[6]

$$E_i = \ln(\beta_2) + Q_i - W_i - \epsilon_{2i} - \ldots_{i}$$

Or, the relationship between employment, wages and output is affected by uncertainty regarding current period productivity and the wage rate.

Combining this first order condition with the production function, we can establish the conditions under which employment will be correlated with the production function disturbance. Specifically, eliminating Q, E may be expressed in terms of exogenous variables and a compound error term:

$$E_i = \ln(\beta_2) + (1-\beta_2)^{-1}[D_i\beta_1 + \alpha K_i^* + \beta_2\ln(\beta_2) - W_i + (\bar{u}_{1i} - \epsilon_{2i})]$$

Hence the observed value of E_i is independent of ϵ_{1i}, and if none of the production disturbance is anticipated (i.e., $\bar{u}_{1i} = 0$ for all i), one may estimate equation (1) without correcting for simultaneity bias (Zellner <u>et al</u>, 1966). Indeed, regardless of whether managers profit maximize, factor inputs can be treated as exogenous when u_1 is completely unobserved. On the other hand, if managers have knowledge of some portion of the disturbance term u_1 at the time that the employment

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6/ The first order condition for <u>expected</u> profit maximization is the same, except in that one-half the variance of ϵ_1 enters additively on the right-hand side (e.g., Zellner <u>et al</u>, 1966). Following Kumbhaker (1987), we assume median profit maximization in order to avoid carrying along this extra term. This assumption will not matter except in section E, as will be discussed below.

decision is made, simultaneity problems must be addressed. This paper develops estimators for each possibility. In sections C and D it is presumed that managers are surprised by realizations on their plant's technical efficiency (relative to industry norms) and the first-order condition for profit maximization is ignored. In section E the first-order condition is incorporated in the model, and simultaneity issues are dealt with.

C. DEALING WITH ERRORS IN VARIABLES

Successful estimation of the production parameters in equation (1) will yield an index of the returns to scale ($\alpha + \beta_2$), the average level of productive efficiency (β_0), and dispersion about the average efficiency level $\text{var}(u_1)=\sigma_1^2$. Most plant-level studies of technical efficiency have focussed on the latter, often attempting to isolate an efficiency component of the residual from pure noise, then comparing variance in this efficiency component across groups of plants or across time.[7] This literature has thus generally been preoccupied with issues such as whether to view u_1 as the sum of a normal and a truncated-normal, a normal and an exponential, or a normal and a gamma error. Accordingly, traditionally reclusive parameters like the third moments

7/ To interpret changes in the variance of u_1 as reflecting changes in technical efficiency, it is necessary to assume that the factors other than efficiency which influence u_1 (e.g., measurement error in Q) are homoskedastic across plants and time. This is standard in "stochastic frontier" representations of production functions.

of disturbances have ascended to prominance in the analysis.[8]

Surprisingly, despite all the attention that has been lavished on the disturbance term, the literature has been silent on how measurement error in the explanatory variables can undermine the whole approach. Specifically, true capital (K^*) is unobservable, and its proxy, the book value of capital (K), is a very crude substitute. Hence part of the disturbance term will reflect capital stock mismeasurement, and the coefficient on capital itself will be biased downward. None of the dimensions of productive efficiency will be correctly measured, and contrasts in measured efficiency across plants or time will reflect such things as the degree to which capital and labor covary. This section develops a correction for these measurement error biases, de-emphasizing the distribution of u_1 in order to do so.

The measurement error problem is not difficult to deal with if we assume that factor inputs can be treated as exogenous, and that the book value of capital is observed for all plants in the sample. For the moment, let us do so. (Both assumptions will be relaxed in following subsections.) Moreover, let us assume that "true" capital stock, K^*, satisfies the following two equations:[9]

8/ When dealing with panel data, it is not necessary to make distributional assumptions on the efficiency component of the error term (e.g., Schmidt and Sickles, 1984; Battese and Coelli, 1988; Cornwell et al, 1988). Other issues that have received considerable attention are: whether to view the inputs as exogenous, and whether to base the analysis on cost functions or production functions.

9/ Hereafter, "i" subscripts will be suppressed when no ambiguity results.

$$(2) \qquad K^* = Z\gamma + L'\delta + u_2$$

$$(3) \qquad K = K^* + u_3$$

In this system, Z is some instrument for the true capital stock (candidates will be discussed later), γ and δ are a scalar and a conformable parameter vector, and u_2 and u_3 are random disturbances, independent of each other and u_1, with zero means and variances $var(u_j) = \sigma_j^2$. The vector L can be included among the instruments for K^* since no exclusion restrictions are required to identify the parameters of interest. (It will become apparent that this inclusion simplifies estimation.)

Combining equations, the system can be collapsed to a reduced form in observable variables:

$$(4) \qquad Q = \alpha\gamma Z + L'(\alpha\delta + \beta) + u_1 + \alpha u_2$$

$$(5) \qquad K = \gamma Z + L'\delta + u_2 + u_3$$

Assuming all disturbances are normal, a non-linear Zellner-Efficient estimator can be used to obtain FIML estimates for systems of this type, imposing cross-equation parameter constraints and recognising the correlation across reduced-form disturbances induced by u_2 (Goldberger, 1972).[10] In the present case, since the above system is exactly identified, the same estimates could be obtained by estimating the projections (4) and (5) as a linear reduced form, then solving for structural parameters in the manner of indirect least squares (ILS).

10/ Of course, the estimator is not FIML if there are missing data problems.

D. DEALING WITH MISSING DATA

The approach described above corrects for bias due to capital stock measurement, but even if we ignore possible simultaneity problems, it is of limited use for developing country analysis because it cannot deal with observations that are missing capital stock values. (In many instances, these missing capital observations can amount to more than half the industry.) At best this makes the estimator inefficient; at worst, if the pattern of missing values is not "ignorable" (e.g., Little, 1982), the Goldberger/ILS estimator is inconsistent.

In principle, these missing data problems could be dealt with by writing the likelihood function for the entire sample (including incomplete observations) in terms of the Greek parameters introduced above, and finding the global maximum. However, such an approach is very difficult to implement. A much more appealing way to obtain maximum likelihood estimates from incomplete data is proposed by Gourieroux and Monfort (1981).[11] Their approach is employed below to develop a variant of the Goldberger/ILS framework.

The Gourieroux/Monfort method amounts to re-expressing one's system as two equations with the following properties: disturbances of the equations are orthogonal, there are no cross-equation parameter constraints, and only one of the equations involves the variable subject to missing values (in the present case, K). FIML estimates of the

11/ For a discussion of the Gourieroux and Monfort methodology and its antecedents, see Griliches (1985).

parameters in this transformed system can be obtained equation by equation, using the entire sample for the equation not involving K, and complete observations only for the other equation. Then, because parameters of the estimated system are functions of the parameters of the original system, the latter can be recovered from the former. Exact identification of the model makes the procedure straightforward.

To begin, as a definitional matter, rewrite equation 4 as:

(6) $Q = Zc + L'b + v_1$, where

$$v_1 = u_1 + \alpha u_2$$

$$b = \alpha\delta + \beta, \qquad c = \alpha\gamma$$

$$a^2 = \text{var}(v_1) = \sigma_1^2 + \alpha^2\sigma_2^2$$

Next, form a linear combination of equations (4) and (5), the weights being μ and 1, respectively:

(7) $K = eQ + L'f + Zg + v_2$, where

$$v_2 = \mu u_1 + (1 + \alpha\mu)u_2 + u_3$$

$$e = -\mu, \qquad f = \mu(\alpha\delta + \beta) + \delta, \qquad g = \gamma(1 + \mu\alpha),$$

$$d^2 = \text{var}(v_2) = \mu^2\sigma_1^2 + (1+\alpha\mu)^2\sigma_2^2 + \sigma_3^2 \quad .$$

Given that Q and K^* are jointly normally distributed (conditional on L and Z), the system (6), (7) is simply another way to write the system (4), (5). Hence, given any (non-zero) value of μ, the Greek parameters of the system (1), (2), (3) can be uniquely obtained from the Roman parameters of the system (6), (7). Or, given μ, the set of Greek parameter values $(\alpha,\beta,\gamma,\delta,\sigma_1{}^2,\sigma_2{}^2,\sigma_3{}^2)$ that maximizes the likelihood function based on (1), (2) and (3) for the entire data set (including incomplete observations) is the same as the set of Greek parameter values implied by the above equalities when the Roman parameter values $(a^2, b, c, d^2, e, f, g)$ maximize the likelihood function based on (6) and (7) for the entire data set.

We are free to choose the unique μ that makes the disturbance v_2 orthogonal to v_1:

$$\mu = -\alpha\sigma_2^2 \, (\alpha^2\sigma_2^2 + \sigma_1^2)^{-1}$$

Then the following one-to-one relationship between Greek and Roman parameters holds:

$$\alpha = c(g + ce)^{-1} \qquad \sigma_2^2 = ea^2(g + ce)/c$$

$$\gamma = g + ce \qquad \sigma_1^2 = a^2[1 - ce(g + ce)^{-1}]$$

$$\beta = b - c(g + ce)^{-1}(f + eb) \qquad \sigma_3^2 = d^2 - e^2a^2[1 - ce(g + ce)^{-1}]$$

$$\delta = f + eb \qquad -[1-ce(g+ce)^{-1}]^2ea^2(g+ce)c^{-1}$$

Moreover, because v_1 and v_2 are constructed to be orthogonal, maximum likelihood estimates for the Roman parameters are easy to construct -- the associated likelihood function factors into a term that involves K and a term that does not:

$$\text{(8)} \qquad L = \prod_{i=1}^{n} \pi_1(Q_i | Z_i, L_i; a^2, b, c) \prod_{i=1}^{n_c} \pi_2(K_i | Q_i, Z_i, L_i; d^2, e, f, g)$$

Here π_1 is the density function associated with equation (6), π_2 is the density function associated with equation (7), n is the size of the entire sample, and n_c is the number of observations that include values for K. (It is assumed the sample is ordered so that these come first.)

Maximum likelihood estimates of the parameters in the first component are simply least squares estimates over the entire sample. If there is no selection bias problem, the parameters of the second component are similarly estimated using the subsample for which K is observed. But if the process which generates missing values is not "ignorable" (e.g., Little, 1982), then the appropriate (d^2,e,f,g) estimator corrects for selectivity bias by replacing $\pi_2(\ )$ with the joint density for K and I (given exogenous variables), where I is a dummy that takes on a value of 1 when K is observed. Specifically, let I^* be an indicator variable such that $I=1$ when $I^*>0$, and $I=0$ otherwise, and express I^* as a function of all variables in the system except K:

$$(9) \qquad I^* = Z\xi_1 + L'\xi_2 + Q\xi_3 + u_4$$

Then if the disturbance u_4 is correlated with v_2, equations (7) and (9) should be estimated jointly using a maximum likelihood package for selectivity correction. Alternatively, if v_2 and u_4 are independent, the missing data pattern can be ignored, even if the vector ξ is nonzero. (Nonzero ξ vectors are likely, given that incomplete reporting is often concentrated among small plants.) Construction of the covariance matrix with or without a selectivity correction is discussed in appendix 1.

It is worth noting that exact identification of the system is really not necessary to implement the general approach of this section. If the system is over-identified, the likelihood function will still take the form of equation 8, but optimization in Roman parameter space will be constrained by the over-identifying restrictions, meaning that equation-by-equation estimation is no longer possible. Bound, Griliches and Hall (1986) discuss estimation of an analogous over-identified system using the method of scoring.

E. ENDOGENOUS EMPLOYMENT

As noted in section B, if firms choose inputs for the current period prior to learning anything about the current period production function disturbance u_1, and if expectational errors regarding relative prices are uncorrelated with other disturbances in the system, factor stocks may be treated as exogenous and the estimators developed in section D above will be consistent. However, so long as managers condition their employment decisions on some component of the current production disturbance, simultaneity issues must be dealt with. If one is willing to assume that plants do not systematically deviate from short-run profit maximization, it is possible to do so by extending the approach of the previous subsection.

The extention amounts to incorporating the first-order condition for profit maximization into the likelihood function. From section B, this condition equates the log of labor's share to the log of the elasticity of output with respect to labor, plus noise:[12]

12/ As mentioned earlier, when expected profit maximization is assumed, one-half the variance of ϵ_1 appears on the right in this expression. Hence, if firms actually maximize expected profits, the assumption of median profit maximization leads to over-estimation of β_2.

(10) $E + W - Q = \ln(\beta_2) + u_5,$

The disturbance term, $u_5 = -\epsilon_1 - \epsilon_2$, reflects optimization errors due to surprises in either prices or productivity. It is the average squared deviation for the optimal labor share, given E, W and Q. Or, presuming there is no industry-wide tendency to over- or under-employ labor, $\text{var}(u_5) = \sigma_5^2$ is an index of <u>ex post</u> allocative efficiency: the larger this variance, the larger the mean-squared deviation from optimal employment levels (e.g., Lau and Youtopoulous, 1971; Schmidt and Lovell, 1979 and 1980).

Earlier discussion sheds light on the covariance of u_5 with other disturbances. Recall that $u_1 = \bar{u}_1 + \epsilon_1$ reflects the combined influence of anticipated and unanticipated output shocks. So if ϵ_1 is not always zero, then $\text{cov}(u_1,u_5) = \rho_{15}$ is nonzero. Similarly, if there is some uncertainty about the stock of <u>true</u> capital, the marginal product of labor that managers perceive will partly reflect unanticipated realizations on u_2. It is thus advisable to let $\text{cov}(u_2,u_5) = \rho_{25}$ be non-zero as well.

Recognizing these features of the covariance matrix for u, we now re-derive our technology estimator. The logic essentially follows that of section D. First, replace L' with [1,D'] in equation 2, so that labor is no longer used as an instrument for true capital.

(2') $K^* = Z\gamma + [1,D']\delta + u_2$

(Hereafter assume the vector $\delta' = [\delta_0,\delta_1']$ conforms to [1,D'].) Next, combine equation (10) with (1') and (2') to eliminate employment, and obtain Q as a function of exogenous variables:

(11) $Q = h_0 + D'h_1 + h_2Z + e_1$

(The implied relation between h and Greek parameters, as well as that between e_1 and u's, will be discussed shortly.) Now rewrite the first-order condition (10) in terms of Roman parameters:

(12) $E + W - Q = m_0 + e_2$

Finally, substitute (2') into (3):

(5') $K = Z\gamma + [1,D']\delta + u_2 + u_3$

and construct a linear combination of the result with equations, (11) and (12); the weights being 1, ψ and λ respectively. This combination can be written with K on the left-hand-side (equation 13), and with appropriate choice of ψ and λ, it has a disturbance orthogonal to disturbances in both these equations:

(13) $K = q_0 + D'q_1 + q_2Z + q_3Q + q_4(E + W - Q) + e_3$

We have now collapsed the structural equations (1), (2'), (3), and (10) to a 3-equation system -- (11), (12), and (13). (Selectivity bias has been ignored for expositional ease only.) Because we are working with cross sectional data, we can assume that plants operate in the same labor market, and that no cross-plant variation in W is observed.[13]

Hence the Roman parameters of this system can be written in terms of Greek parameters as:

(14) $h_0 = [\beta_0 + \beta_2(\ln\beta_2 - W) + \alpha\delta_0]/(1-\beta_2)$ $\qquad q_0 = \delta_0 + \psi h_0 + \lambda m_0$

$h_1 = [\beta_1 + \alpha\delta_1]/(1-\beta_2)$ $\qquad q_1 = \delta_1 + \psi h_1$

$h_2 = \alpha\gamma/(1-\beta_2)$ $\qquad q_2 = \psi h_2 + \gamma$

$m_0 = \ln(\beta_2)$ $\qquad q_3 = -\psi$

$q_4 = -\lambda$

Also, the disturbances of this system can be written as:

$$e_1 = [u_1 + \alpha u_2 + \beta_2 u_5]/(1-\beta_2)$$

$$e_2 = u_5$$

$$e_3 = u_2 + u_3 + \psi[u_1 + \alpha u_2 + \beta_2 u_5]/(1-\beta_2) + \lambda u_5$$

If zero restrictions are imposed on all $\mathrm{cov}(u_i, u_j) = \rho_{ij}$ except ρ_{15} and ρ_{25}, elements of the variance-covariance matrix for e_j's are:

13/ This assumption may not be a good one if plant locations vary widely, but region-specific variations in labor markets are likely to be intermingled with other features of the local economy, all of which are picked up by regional dummies. In the absence of detailed data on employment and wages by type of worker and region, letting regional wage variation be picked up by dummies seems the least restrictive approach -- it should minimize the extent to which wage variation contaminates parameter estimates.

$$\mathrm{var}(e_1) \equiv s_1^2 = \left[\sigma_1^2 + \alpha^2\sigma_2^2 + \beta_2^2\sigma_5^2 + 2(\beta_2\rho_{15} + \alpha\beta_2\rho_{25})\right]B^2$$

$$\mathrm{var}(e_2) \equiv s_2^2 = \sigma_5^2$$

$$\mathrm{var}(e_3) \equiv s_3^2 = \left[\psi^2B^2\sigma_1^2 + (1+\alpha B\psi)^2\sigma_2^2 + \sigma_3^2 + (\psi B\beta_2 + \lambda)^2\sigma_5^2\right]$$
$$+ 2\left[\psi B(\psi B\beta_2 + \lambda)\rho_{15} + (\psi^2B^2\alpha\beta_2 + \psi B\beta_2 + \psi B\lambda\alpha + \lambda)\rho_{25}\right]$$

$$\mathrm{cov}(e_1,e_2) \equiv s_{12} = B(\rho_{15} + \alpha\rho_{25} + \beta_2\sigma_5^2)$$

$$\mathrm{cov}(e_1,e_3) \equiv s_{13} = \psi s_1^2 + B(\alpha\sigma_2^2 + \beta_2\rho_{25}) + \lambda B(\alpha\rho_{25} + \beta_2\sigma_5^2 + \rho_{15}) = 0$$

$$\mathrm{cov}(e_2,e_3) \equiv s_{23} = \psi s_{12} + \rho_{25} + \lambda\sigma_5^2 = 0.$$

Here $B = 1/(1-\beta_2)$ and $\mathrm{cov}(e_1,e_3) = \mathrm{cov}(e_2,e_3) = 0$ by choice of λ and μ, as in the simpler model of section D.

The dimension of the vector $(\beta,\alpha,\delta,\gamma,\psi,\lambda)$ is the same as that of (h,m,q), and there is a one-to-one relationship between these vectors, based on (14). Also, the six elements of the variance-covariance matrix for e can be used to identify $(\sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_5^2, \rho_{15}, \rho_{25})$. Thus, there is exact identification of the Greek parameters in terms of Roman parameters, and as before, maximum likelihood estimators for the former can be obtained from maximum likelihood estimators for the latter (see appendix 2). Roman ML estimates can be obtained by fitting equations (11) and (12) as a seemingly unrelated system (e.g., using an iterative Zellner algorithm), and applying OLS to equation (13). The likelihood function for the Roman parameters is:

$$L = \prod_{i=1}^{n} \pi_1(Q,E+W-Q|D,Z;h,m_0,s_1^2,s_2^2,s_{12}) \prod_{i=1}^{n_c} \pi_2(K|Q,E+W-Q,D,Z;n,s_3^2)$$

If data are not missing randomly, then selectivity bias can be corrected as described in the previous section.

F. AN APPLICATION TO CHILEAN INDUSTRIAL CENSUS DATA

In sections D and E two approaches have been developed that deal with missing capital stock data and errors in capital stock measurement. The first approach presumes that managers cannot condition their labor input choice on current period production shocks; the second approach assumes that at least part of this shock is anticipated, and invokes first-order conditions for profit maximization. In this section both approaches are applied to 1979 Chilean industrial census data, and compared with two references cases: OLS estimates based on complete data subsamples (assuming no measurement error in capital), and the Goldberger/ILS estimator reviewed in section C. Also, to gauge the significance of selectivity bias, estimates with selectivity corrections are constructed for the "section D" estimator.

Each of the estimators described above is applied to data from five industries: food (ISIC code 312), beverages (ISIC code 313), leather products (ISIC 323), footwear (ISIC code 324) and printing (ISIC 342). These industries are chosen because they exhibit substantial missing data on capital stocks and they span a range of sample sizes. Variable definitions are provided in table 1, a more complete description of the data base can be found in Tybout, de Melo, and Corbo (1989).

Table 1: Variable Definitions

Q = value added corrected for inflation distortions[14]

E = labor input, expressed in efficiency units[15]

D_1 = 1 if the firm is a proprietorship, 0 otherwise

D_2 = 1 if the firm is a partnership, 0 otherwise

D_3 = -1 if the firm is among the smallest third of the industry samplo; 0 if the firm is among the middle third of the industry sample; and 1 if the firm is among the largest third of the industry sample[16]

K = reported value of the capital stock, or machinery and equipment plus vehicles, plus land and buildings. (This variable is considered "missing" if at least one component takes a zero or missing value.)

Z = machinery and equipment[17]

14/ See Tybout, deMelo, Corbo (1989) for details of the correction procedure

15/ This variable is constructed as the wage bill divided by the minimum wage. The wage bill includes an imputation for owners and family help. See Griliches and Ringstad (1971) for a similar definition. In earlier work with this data base, Corbo and deMelo (1985) tested several specifications of the labor variable to deal with heterogeneity in the labor force and found that labor input measured by the total number of unskilled equivalent workers was the best.

16/ See Maddala (1977) for a discussion of this instrument in the context of errors in variables.

17/ We choose this instrument because when total capital is missing, it is usually because the plant has rented its buildings, land or vehicles -- machinery and equipment is almost always reported. Moreover, most of the measurement error in capital stock should come from buildings, land, and intangibles. In other data bases, preferable instruments may be available -- installed horsepower is one example.

Table 2: Alternative Estimators of Production Technology*

industry	n_c	n	$\hat{\alpha}$	$\hat{\beta}_0$	$\hat{\beta}_2$	$\hat{\sigma}_1^2$	$\hat{\sigma}_2^2$	$\hat{\sigma}_3^2$	$\hat{\alpha} + \hat{\beta}_2$
<u>**OLS: Complete Data Only**</u>									
food	696	--	.275	2.86	.738	.82	--	--	1.013
			(.041)	(.265)	(.062)				
beverages	74	--	.201	3.36	.916	.98			1.117
			(.151)	(1.21)	(.223)		--	--	
leather products	40	--	.335	3.25	.585	.51	--	--	.920
			(.207)	(1.04)	(.296)				
footwear	57	--	.225	2.47	.792	1.70	--	--	1.017
			(.269)	(1.75)	(.315)				
printing	106	--	.157	3.67	.837	.54	--	--	.994
			(.097)	(.573)	(.127)				
<u>**ILS/Goldberger: Complete Data, Errors-in-Variables**</u>									
food	696	--	.318	2.68	.689	.82	.13	.09	1.007
			(.050)	(.290)	(.070)	(.046)	(.053)	(.053)	
beverages	74	--	.252	3.06	.866	.97	.05	.13	1.119
			(.172)	(1.27)	(.231)	(.161)	(1.94)	(.195)	
leather products	40	--	.535	2.49	.346	.49	-.04	.13	.882
			(.224)	(1.07)	(.308)	(.105)	(.059)	(.065)	
footwear	57	--	.125	2.98	.878	1.71	.49	-.37	1.003
			(.300)	(1.84)	(.329)	(.325)	(.982)	(.499)	
printing	106	--	.111	3.86	.883	.55	.33	-.23	.995
			(.103)	(.584)	(.131)	(.076)	(.207)	(.204)	

* Standard errors, when calculated, are in parentheses.

Table 2 (con't): Alternative Estimators of Production Technology*

industry	n_c	n	$\hat{\alpha}$	$\hat{\beta}_0$	$\hat{\beta}_2$	$\hat{\sigma}_1^2$	$\hat{\sigma}_2^2$	$\hat{\sigma}_3^2$	$\hat{\alpha} + \hat{\beta}_2$
Section D without Selectivity Correction									
food	696	1880	.329	2.72	.632	.80	.12	.10	.961
			(.028)	(.179)	(.042)	(.028)	(.051)	(.051)	
beverages	74	138	.315	2.52	.783	1.09	.05	.13	1.098
			(.113)	(.907)	(.171)	(.132)	(.164)	(.165)	
leather products	40	109	.482	2.53	.364	.69	-.06	.15	.847
			(.108)	(.685)	(.181)	(.091)	(.078)	(.083)	
footwear	57	266	.200	2.82	.793	1.17	.21	-.09	.994
			(.109)	(.674)	(.142)	(.104)	(.257)	(.254)	
printing	106	388	.183	3.55	.755	.63	.23	-.13	.938
			(.046)	(.295)	(.072)	(.047)	(.134)	(.132)	
Section D with Selectivity Correction									
food	696	1880	.266	3.30	.663	.80	.27	.17	.930
			(.022)	(.144)	(.034)				
beverages	74	138	.261	2.88	.831	1.18	.06	.13	1.092
			(.097)	(.844)	(.165)				
leather products	40	109	.472	2.63	.370	.76	-.07	.16	.842
			(.108)	(.696)	(.182)				
footwear	57	266	.205	2.86	.779	1.22	.19	-.06	.984
			(.101)	(.643)	(.138)				
printing	106	388	.134	4.02	.763	.67	.26	.04	.898
			(.035)	(.252)	(.069)				
Section E without Selectivity Correction									
food	696	1880	.242	14.55[a]	.418	.86	.29	.20	.660
beverages	74	138	.283	11.30[a]	.252	1.32	.19	.07	.534
leather	40	109	.242	13.19[a]	.346	.74	.06	.43	.588
footwear	57	266	.252	15.14[a]	.451	1.23	.34	.16	.702
printing	106	388	.277	12.55[a]	.316	.74	.27	-.07	.594

* Standard errors, when calculated, are in parentheses.

a This coefficient depends upon the assumed price of unskilled labor, which is arbitrary in cross-sectional work.

Table 2 presents results. The first panel gives OLS production function estimates based on complete data subsamples. Next are Goldberger/ILS estimates for complete data subsamples (panel 2), the section D estimator without a selectivity bias correction (panel 3), the section D estimator <u>with</u> a selectivity correction (panel 4), and finally, the section E estimator without a selectivity correction (panel 5).

The first issue to consider is whether capital stock measurement error is signficant. If it is, one would expect the coefficient on capital to shift upward when the error is instrumented out, and one would expect to observe a positive estimated value for σ_3^2. Both of these results are observed for three of the five industries considered (food, beverages, and leather); neither result is observed for the remaining two (footwear and printing). Hence, the correction for measurement error appears to often generate the desired result, but not always.[18] The reason is presumably that the instrument is better for some industries than for others, and measurement error is more important in some industries than others. Surprisingly, correction for measurement error appears to leave the variance of the production

18/ In an application of the section D estimator to 21 3-digit industries for two different census years, 15 of the 42 estimates for σ_3^2 were negative (Tybout, deMelo and Corbo, 1989). Only four of these 15 were greater than their standard errors in absolute value, and only two were greater than twice their standard error. Among the positive estimates for σ_3^2, 15 exceeded their standard error, and 8 exceeded twice their standard errors.

function disturbance u_1 virtually unchanged. Finally, although parameters of the production function are influenced by the correction for measurement error, estimates of returns to scale (i.e., $\alpha+\beta_2$) are much less sensitive. That is, the correction shifts elasticities between the two factors more than it changes the sum of the elasticities.[19] (For this reason, the effect on intercept terms is small relative to their standard errors.) So the bias introduced by measurement error is more likely to undermine analyses of marginal productivities than to affect scale or technical efficiency comparisons.

Consider next the potential contribution of observations for which capital is unobserved. Our "section D" estimator exploits these incomplete observations while correcting for measurement error. Note that, compared to either the OLS or the ILS/Goldberger estimator, it yields substantially lower standard errors, both for the labor <u>and</u> the capital coefficient. Whereas most of the capital coefficients (α) were insignificant by the usual standards for ILS estimates, <u>all</u> are at least twice their standard errors when the "section D" estimator is employed. It would appear that incomplete data can be very important -- even when the complete data subsample is large. Returns to scale also fall slightly for each sector, and more strikingly, the estimated variance of

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<u>19</u>/ This is reminiscent of the Griliches and Ringstad (1971) finding that measurement errors "biased the estiamted elasticity significantly downwards, [but] their effect on the estimated scale coefficient is quite small" (p. 99).

the production function disturbance (u_1) is affected.[20] Hence conclusions regarding technical efficiency are likely to be significantly influenced by the exclusion of incomplete observations.

If there is selectivity bias in the pattern of missing data, the OLS, ILS, and Section D estimators are all inconsistent. To gauge the significance of this problem, refer next to the corrected figures. Notice first that, while there is some effect, the labor and capital coefficients do not appear very sensitive to selectivity correction. Returns to scale are even less senstive: the correction shifts relative weights between labor and capital, leaving the sum of the weights to fall only slightly. (The intercept rises slightly to compensate.) As with measurement error corrections, estimates of σ_1^2 are not strongly affected. In short, selectivity bias appears to make some difference, but the effect is not dramatic.

Finally, consider the "section E" estimator, which treats labor as endogenous and assumes firms maximize median profits. Here, imposition of the extra structure typically increases the capital coefficient somewhat, but it pulls down the labor coefficient a great deal, resulting in implausibly low returns to scale in all industries. The reason that labor's coefficient drops is straightforward -- it is pinned down by equation 10, which equates labor's share to the

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20/ One should bear in mind that maximum likelihood estimators do not correct for degrees of freedom, and the ILS estimator is based on a much smalller number of observations than the "section D" estimator. Nonetheless, the ILS variance estimates are not generally smaller than the corresponding "section D" figures.

elasticity of output with respect to labor. Since capital's coefficient is not similarly pinned down, we are left with the impression that firms would do well to scale down their operations as rapidly as possible. It is not clear why the estimator works so poorly, but there are several possibilities. One is that this approach leans too heavily on the unit elasticity of substitution implied by Cobb-Douglas production functions. Another is that firms simply do not pay labor its marginal product -- perhaps because of adjustment costs. A third possibility is that there are significant measurement errors in labor. Whatever the explanation, there can be little doubt that this estimator is not useful in its present form.

A brief summary of the findings may be helpful. First, measurement error is often empirically important, and correcting for it affects the relative size of output elasticities. However, returns to scale do not seem sensitive to measurement error correction, at least not with the capital stock instrument used here. Second, the use of incomplete observations can dramatically improve the efficiency of estimators; it also signficantly changes estimates of the cross-plant dispersion in productivity. Third, the selectivity bias that results from assuming that missing data patterns are "ignorable" does not appear to be dramatic. Finally, exploitation of first-order conditions to treat employment as endogenous clearly imposes too much structure on the system. Overall, it appears that the Section D estimator (with or without selectivity corrections) is the most reasonable approach.[21]

21/ Elsewhere I have applied the section D estimator with good results to the issue of trade regimes and industrial productivity (Tybout, de Melo and Corbo, 1989).

Appendix 1: The Variance-Covariance Matrix

It remains to derive the covariance matrix for the Greek parameter estimators derived above. Consider first the case in which labor is treated as exogenous. If there is no selectivity bias, the asymptotic information matrix, B, can be derived from (8):

$$B = -\underset{n\to\infty}{\text{plim}}\ E\left(\frac{\partial\ \ln(L)}{\partial\phi\ \partial\phi'}\right) = \frac{1}{a^2}\left\{\left(\frac{\partial q'}{\partial\phi}\right)\Omega\left(\frac{\partial q}{\partial\phi'}\right) + \frac{1}{2a^2}\left(\frac{\partial a^2}{\partial\phi}\right)\left(\frac{\partial a^2}{\partial\phi'}\right)\right\}$$

$$+ \frac{\theta}{d^2}\left\{\left(\frac{\partial k'}{\partial\phi}\right)\begin{bmatrix} q'\Omega q+a^2 & q'\Omega \\ \Omega h & \Omega \end{bmatrix}\left(\frac{\partial k}{\partial\phi'}\right) + \frac{1}{2d^2}\left(\frac{\partial d^2}{\partial\phi}\right)\left(\frac{\partial d^2}{\partial\phi'}\right)\right\}$$

where: $\phi' = (\alpha,\beta,\gamma,\delta,\sigma_1^2,\ \sigma_2^2,\ \sigma_3^2)$

$q' = (b',c)$

$k' = (e,f',g)$

$\Omega = \text{plim}\ n^{-1}\begin{bmatrix} L'L & L'Z \\ Z'L & Z'Z \end{bmatrix}$

$\theta = \text{plim}\ n_c/n$

And using this matrix, the asymptotic variance of Greek estimators can be constructed as the Cramer-Rao lower bound:

$$\text{asm var}(\sqrt{n}\ \hat{\phi}) = B^{-1}$$

(Hats denote estimators for the population parameters.) Alternatively, whether there is selectivity bias or not, the covariance matrix for Greek parameter estimators can be derived as a quadratic function of the covariance matrix for the Roman parameter estimators:

$$\mathrm{var}(\hat{\phi}) = \begin{bmatrix} \partial\phi'/\partial q^* \\ \partial\phi'/\partial k^* \end{bmatrix}' \begin{bmatrix} \mathrm{var}(\hat{h}^*) & 0 \\ 0 & \mathrm{var}(\hat{k}^*) \end{bmatrix} \begin{bmatrix} \partial\phi'/\partial q^* \\ \partial\phi'/\partial k^* \end{bmatrix}$$

where:

$$q^{*\prime} = (b', c, a^2)$$

$$k^{*\prime} = (e, f', g, d^2)$$

This expression exploits the fact that $\hat{q}^*$ and $\hat{k}^*$ are orthogonal estimators, which of course follows from the factorization of the likelihood function. It has the advantage of allowing simple variance construction in the case where selectivity bias is accounted for.[22] Similar expressions with appropriate redefinitions of q, k, and ϕ can be derived for the case in which labor is endogenous and profit maximization (up to random measurement error) is assumed:

$$q' = [h', m_0, s_1^2, s_2^2, s_{12}]$$

$$k' = [q', s_3^2]$$

$$\phi' = [\alpha, \beta', \delta', \psi, \lambda, \sigma_1^2, \sigma_2^2, \sigma_3^2, \sigma_5^2, \rho_{12}, \rho_{25}]$$

22/ Since it is equivalent to the first variance expression when there is no selectivity treatment, both estimators can be constructed without a selectivity correction and compared to one another as a programming check. This was done for the reported figures.

Appendix 2: Greek Parameters for the Endogenous Labor Model

This appendix presents the mapping from Roman to Greek parameters for the "section E" estimator. Let $B = 1/(1-\beta_2)$. Then:

$$\phi = -q_3 \qquad \lambda = -q_4$$

$$\delta_0 = q_0 + q_3h_0 + q_4m_0 \qquad \gamma = q_2 + q_3h_2$$

$$\delta_1 = q_1 + q_3h_1 \qquad \alpha = h_2[1-\exp(m_0)]/(q_2 + q_3h_2)$$

$$\beta_2 = \exp(m_0)$$

$$\beta_0 = h_0(1-\beta_2) - \alpha\delta_0 - \beta_2(m_0 - W)$$

$$\beta_1 = h_1[1-\beta_2] - \alpha\delta_1$$

$$\rho_{12} = \rho_{13} = \rho_{23} = \rho_{35} = 0 \text{ (by assumption)}$$

$$\rho_{25} = -(\phi s_{12} + \lambda s_2^2)$$

$$\rho_{15} = s_{12}(1-\beta_2) - \beta_2 s_2^2 - \alpha\rho_{25}$$

$$\sigma_2^2 = [(\phi s_1^2 + \lambda s_{12})(1-\beta_2) + \beta_2\rho_{25}]/\alpha$$

$$\sigma_1^2 = s_1^2(1-\beta_2)^2 - \alpha^2\sigma_2^2 - \beta_2^2 s_2^2 - 2(\alpha\beta_2\rho_{25} + \beta_2\rho_{15})$$

$$\sigma_3^2 = s_3^2 - \phi^2B^2\sigma_1^2 - (\phi\alpha B + 1)^2\sigma_2^2 - (\phi\beta_2 B + \lambda)^2 s_2^2$$
$$-2\phi B(\phi B\beta_2 + \lambda)\rho_{15} - 2(\phi^2B^2\alpha\beta_2 + \phi B\beta_2 + \phi B\lambda\alpha + \lambda)\rho_{25}$$

$$\sigma_5^2 = s_2^2$$

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